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Bridging the Education–Employment Gap in Europe: An AI-Driven Approach to Skill Matching

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Abstract

Education–employment mismatch represents a persistent structural issue across Europe, especially among young people. In line with the digital transformation, green transformation and population aging, new jobs are emerging every day, and some of the older jobs are disappearing. However, existing skills of job seekers may not fit these new jobs. This article presents results from the EMLT + AI project, which aimed to explore how artificial intelligence (AI) tools could contribute to reducing such mismatches and supporting inclusive labor market integration. Based on a sample of 1039 participants across European countries, we analyzed the alignment between individuals' educational background and their current employment, as well as their willingness to reskill. Using binary logistic regression models, the study identifies key factors influencing mismatch and reskilling motivation, including educational level, type of occupation, the presence of meaningful career guidance, and AI-based job search practices. The results indicate that individuals who hold a master's degree and work in positions requiring at least bachelor's level degrees are more likely to be matched with jobs that align with their field of study. However, access to mentoring remains limited. The paper concludes by proposing an AI-supported training model integrating career recommendation systems, flexible learning modules, and structured mentoring. These findings provide empirical evidence on how emerging technologies can foster more responsive and adaptive education-to-employment transitions, contributing to policy innovation and the development of inclusive digital labor ecosystems in Europe.

Keywords: education–employment mismatch; artificial intelligence; reskilling motivation

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1. Introduction

Career decision-making is a foundational process in an individual's professional development. It directly affects not only one's income and job satisfaction but also broader aspects such as financial stability, quality of life, and societal engagement [1–5]. As the complexity of labor markets increases and economic systems become more dynamic, young individuals are often confronted with a multitude of potential career paths. This variety, while seemingly advantageous, can create confusion and uncertainty, particularly in the absence of structured career guidance. Moreover, transformations driven by the digital revolution, climate crises, and population aging are giving rise to new types of jobs that demand new skills. Digitalization is expected to induce both job creation and destruction, as automation reduces demand for routine tasks while increasing the need for advanced digital competencies [6]. The green transition is likely to generate employment in renewable energy, sustainable production, and environmental services, but also entails displacement risks in carbon-intensive sectors, necessitating large-scale reskilling initiatives [7,8]. Population aging, by contrast, exerts downward pressure on the labor supply, intensifies labor shortages, and expands demand for healthcare and care-related services [9]. Taken together, these dynamics are likely to increase demand for new jobs and skills. Many students make career decisions without professional advice about these changes or access to reliable labor market information, which increases the likelihood of selecting a path misaligned with their skills, interests, or long-term goals.

The resulting education–job mismatch—where individuals are employed in positions that do not align with their academic qualifications or personal aptitudes—is a persistent issue with significant consequences. Mismatches can lead to job dissatisfaction, higher turnover, underemployment, and reduced productivity [10–16]. For workers, the lack of alignment with their training often leads to diminished motivation and limited career advancement. For employers, the impact is also substantial: mismatched hires require more on-the-job training, result in lower performance, and increase human resource costs. These problems are especially acute among youth, a group disproportionately affected by labor market barriers and volatile employment conditions.

In response to this challenge, the Solution Proposal for Education–Job Mismatch Within European Region by Using Artificial Intelligence Algorithms: (EMLT + AI project) was developed. The project aimed to reduce education–job mismatch by building digital career guidance via an AI-based job recommendation system and training ecosystem. Furthermore, the project supported personalized mentoring between young people (between the ages of 18 and 29) and professionals. The core of the solution is an AI-based matching tool that recommends personalized career paths based on an individual's educational background, skill profile, and personal interests. Participants also received tailored training and mentoring support to prepare them for the proposed job tracks. A total of 1039 individuals across several European countries and Turkey participated in a survey conducted within the project.

In January 2022, the EMLT + AI project received approval from the European Union National Agency as a strategic partnership in the field of youth, under project number 2021-1-TR01-KA220-YOU-000028888. By August 2021, Anadolu University's ARİNKOM Technology Transfer Office had accepted the project into its academic venture development program. In March 2022, the project was presented to investors at the TECH-UP meeting in Istanbul.

Young people aged between 24 and 29 are three times more likely to face unemployment compared to adults [17]. This is a significant issue affecting both European Union countries and Turkey. The EMLT + AI project seeks to establish an international platform utilizing artificial intelligence (AI) to enhance the career paths of professionals and young people. The platform offers mentorship opportunities, company network matching, and fosters personal development [17].

The project, led by Anadolu University (Turkey), included the following entities as partners: (Turkey): Eskisehir Chamber of Industry, European Mentoring & Coaching Council, U2C (University to Career) (Turkey), Tagusvalley (Portugal) and University of Extremadura (Spain). This project was based on the premise that career satisfaction is not merely a matter of employment but of fitness between the person and the job. Studies show that individuals who align their work with their skills and values are more engaged and satisfied, which in turn enhances organizational outcomes [17–21]. In the same way, bad hiring decisions cost companies dearly. The average cost of a bad hire can reach 30% of the employee's first-year earnings [22]. These costs arise not only from turnover and retraining but also from lower morale, disrupted team dynamics, and missed business opportunities.

EMLT-AI addresses these inefficiencies by incorporating both jobseekers and employers into its matching process. For jobseekers, particularly those from marginalized groups such as women, migrants, or individuals facing economic and social obstacles, the platform offers structured pathways into meaningful employment. For employers, it improves recruitment accuracy by aligning candidate profiles with specific job requirements using objective and interpretable criteria. This dual approach reflects the project's emphasis on inclusivity and systemic change. To summarize, the research questions of this study are as follows:

1. What are the factors that determine education–employment mismatch?
2. To what extent do the use of AI in the job-search process, the receipt of mentoring services, and the motivation to reskill to find a job or to start one's own business affect education–job mismatch?" The main aim of this paper is to identify the factors affecting skills mismatch for young job seekers in Europe and to discuss how AI tools can contribute to reducing mismatches. To this aim, survey data from over a thousand participants across Europe is analyzed using logit and probit models.

The project design comprised seven interlinked research and implementation phases. These included (1) theoretical analysis of career choice and its socio-economic implications; (2) exploration of the education–job mismatch and its relation to labor productivity; (3) review of youth unemployment and NEET statistics, especially among women; (4) empirical modeling using binary logistic regression to identify mismatch determinants from the 1039 participant dataset; (5) design and implementation of the AI career-matching algorithm; (6) deployment of a training and mentoring system; and (7) evaluation of the AI tool's effectiveness in improving employment alignment and readiness for reskilling.

This paper presents the findings of these phases, with a focus on how AI can enhance labor market integration and career satisfaction among vulnerable youth populations. The analysis offers insights for policymakers, educators, and labor market actors seeking scalable, evidence-based solutions to education–job mismatch.

2. Literature Review on Skills Mismatch and Artificial Intelligence Usage to Recommend Jobs

Since the early 1990s, advancements in Information and Communication Technologies (ICT) have significantly influenced labor market dynamics and driven digital transformation across economies worldwide. The proliferation of internet access, combined with the emergence of cloud-based digital technologies, has facilitated new forms of work organization, including remote and hybrid working models. This transformation has also enabled the digitalization of various labor market processes, ranging from recruitment to internships and vocational training, thereby reshaping the structure and functioning of employment systems [6,23,24].

Digital transformation involves adapting core technologies like big data, AI, and cloud computing to optimize resources, boost efficiency, and drive innovation—creating new competitive advantages and greater resilience to uncertainty [25]. The green transition, aligned with global sustainability goals, is generating new opportunities in renewable energy, energy efficiency, and circular economy models, while also requiring the reskilling of workers from carbon-intensive sectors. The increasing severity of environmental issues linked to change has transitioned toward a sustainable economy and promoted energy production from renewable resources. This shift has also created significant opportunities for green jobs. According to Esposito et al. [26], investments in the green economy and sustainable energy in Europe have stimulated innovative and sustainable employment opportunities, reshaping the labor market. They also emphasize that the rapid expansion of the renewable energy sector is driven by government incentives, technological advancements, and heightened environmental awareness. Moreover, green jobs require specialized skills, particularly in the design, development, installation, and maintenance stages. The importance of the green economy underscores the necessity for young people entering the labor market to strengthen their competencies and acquire relevant skills to remain competitive.

Given the key role of human resources in ensuring sustainability, organizations should also ensure that their employees develop a thorough understanding of environmental issues. To this end, they should prepare their employees by providing the necessary training. The term ‘green training’ is used to describe training and development programs for employees that focus on environmentally sustainable practices [27]. Despite a 12% global increase in employees acquiring green skills between 2022 and 2023, demand continues to outstrip supply. The number of job postings requiring at least one green skill increased by around 22% over the same period. Prioritizing green skills is crucial in order to capitalize fully on the opportunities created by the green transition, utilizing them in a fair and inclusive manner [28]. At the same time, demographic changes—such as population aging, migration, and evolving workforce diversity—are influencing labor supply, work organization, and social protection systems. These interconnected transformations present both opportunities and challenges for policymakers, businesses, and individuals, emphasizing the need for adaptive education systems, lifelong learning, and inclusive labor market policies to ensure resilience and competitiveness in the future economy.

Job Search and Mismatch Theories

Since the 1960s, the relationship between individuals’ skills and their employment outcomes has been extensively conceptualized within economic theory. One of the most influential approaches, human capital theory [25,29,30] interprets skills—primarily acquired through education—as a form of productive resource that can generate economic returns. Within this framework, individuals are viewed as investors who allocate money, labor, and time to develop their skills, with the expectation of converting these investments into higher income in the future. Accordingly, skills and credentials are regarded as the primary assets of job seekers in the labor market.

Based on the above outlined theoretical literature, there is also a growing research on the skills mismatch of employees and their jobs for the last few decades [31,32]. It is argued that as the acceleration of technological developments increases, more and more jobs require new skills [6,23,33]. As a result of globalization, demographic change, digital transformation and green transformation, either the skills needed in the existing jobs are changing or there are new jobs emerging every day.

Digitalization and the green transition are fundamentally reshaping job content and altering the demand for skills. Task-based analyses highlight that ICT tends to displace routine, middle-skill tasks while reinforcing problem-solving and interpersonal competencies, thereby fostering growth not only in high-skill occupations but also in emerging “new middle-skill” roles that integrate technical and service-oriented capacities [24,34]. At the same time, while digital technologies enhance productivity and foster job creation, they also intensify labor market polarization, which underscores the growing importance of reskilling and upskilling to enable workers to adapt to evolving occupational structures. Skills policy discourse increasingly emphasizes the development of lifelong learning pathways that can facilitate the transition of workers, particularly those employed in routine jobs, into higher value-added activities within expanding sectors [35].

The extant literature reveals several factors influencing skills mismatching. Job seekers may not find the matching jobs to their skills, or they may not develop necessary skills due to missing information [36], geographical limitations [37] or various demographic factors [38–44]. Moreover, skills mismatch can have negative effects on both employees and employers, and society in general [21,32,45–47]. Thus, overcoming skills mismatches benefits both sides of the job market and society. In this sense AI tools can help overcome skills mismatches, but despite their growing importance, the application of AI to job recommendation remains limited. Some notable contributions are the work of Paparrizos et al. [2], Razak et al. [1], Almalis et al. [48], and Jain and Kakkar [49], who employed AI to suggest suitable occupations for individuals.

The rapid growth of online information has intensified the need for technologies that assist users in managing information overload. Recommender systems respond to this need by drawing on user and item data to identify relevant options [50]. Such systems underpin decision-making across diverse domains—including e-commerce (e.g., Amazon), social networks (e.g., Facebook, LinkedIn), and employment platforms—by tailoring suggestions for goods, services, or jobs [48].

Parallel to these developments, vocational and technical training increasingly relies on information and communication technologies to optimize career guidance [51]. AI, encompassing machine learning (ML) methods such as k-nearest neighbor, naive Bayes, decision trees, logistic regression, k-means, support vector machines, and neural networks, has become central to modelling educational and occupational choices [52]. Recent work highlights ML's capacity to support learners in selecting educational domains aligned with career aspirations [3].

Regarding the use of AI tools in skills matching, empirical studies illustrate diverse approaches. Paparrizos et al. [2] developed a supervised ML model predicting job transitions using large-scale online profile data. Razak et al. [1] applied fuzzy logic to create a web-based career path recommendation system for Malaysian students, integrating personality and skill assessments. Almalis et al. [48] proposed the Four Dimensions Recommendation Algorithm (FoDRA), which scores candidate-job fit across multiple attribute categories. Jain and Kakkar [49] utilized data mining techniques to match candidates and jobs based on education, skills, industry, and other features. Similarly, Özcan and Öğüdücü [53] designed a reciprocal recommendation system using job application data from a career website.

Nevertheless, AI adoption in recruitment remains underdeveloped. While some firms apply AI to analyze applicants' facial expressions, voices, and gestures, and others (e.g., Google Job API, LinkedIn) provide automated matching services, comprehensive systems that align multifaceted applicant profiles with job characteristics are lacking. Based on the extant theoretical and empirical knowledge outlined above, the EMLT-AI project aims to fill this void by analyzing correlations between individual attributes and occupational requirements, thereby extending recruitment practice.

3. Data and Descriptive Statistics

The data have been collected from the survey of the Erasmus + KA2 Project titled "Solution Proposal for Education–Job Mismatch Within European Region by Using Artificial Intelligence Algorithms; EMLT + AI". Ethics committee permission was obtained from Anadolu University before the survey data were collected, and from UNEX with the Code 282/2024.

The survey was carried out with a total of 1039 participants. Among them, 72.7% are students, 17.6% are employed, 6.9% are unemployed, and 1.4% are NEET (not in education, employment, or training). The results of the questionnaire are shown in the figures below. The survey was conducted with 621 participants from Turkey, 310 participants from Spain, 28 participants from Portugal, 19 participants from Azerbaijan, and 54 participants from other countries (Figure 1).

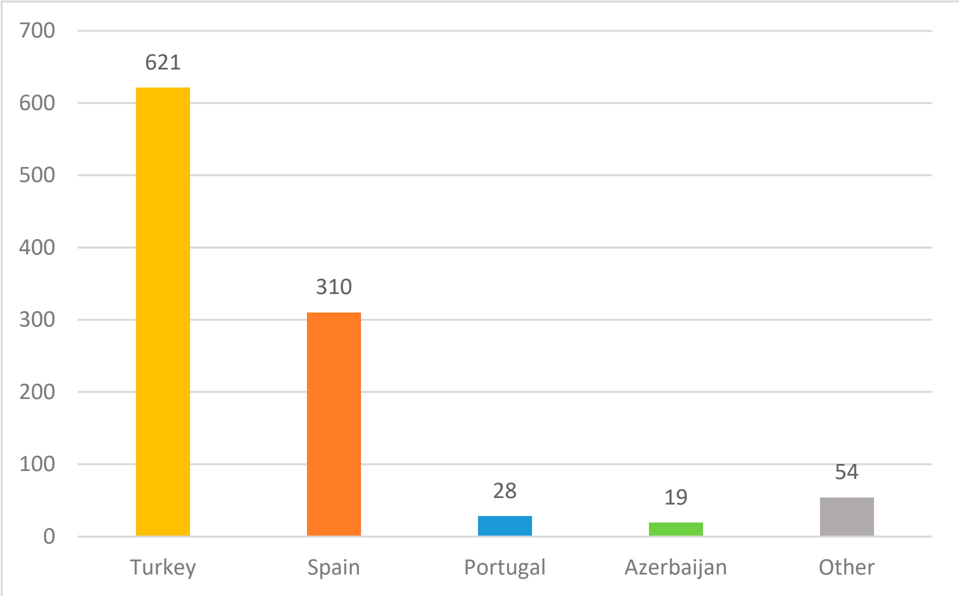

Figure 1. Nationality of the Survey Participants. Source: Authors' calculations based on the primary data.

Figure 2 shows that 59.8% of the participants are male (617 people) and 39.8% (411 people) of the participants are female. A total of 72% of the participants were between the ages of 17–24, 15% were between the ages of 24–30 and 12.5% were over 30 years. In addition, 98% of the participants had no disability.

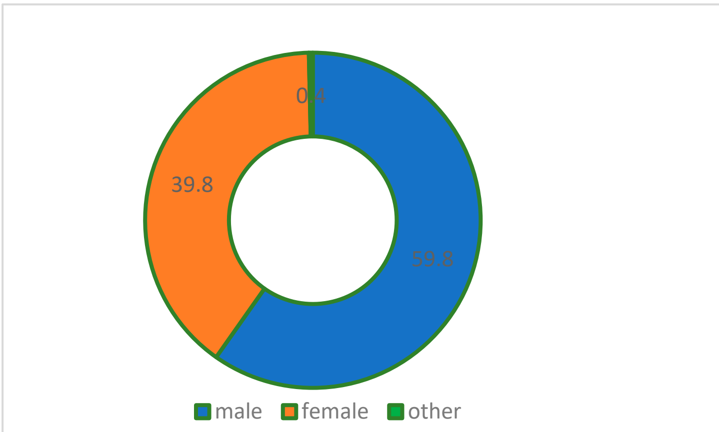

Figure 2. Gender of the Participants (%). Source: Authors' calculations based on the primary data.

Figure 3 shows that 28% of the respondents (283 people) were from the University of Extremadura. 15% of respondents were from Anadolu University, while Eskisehir Technical University and Zonguldak Bulent Ecevit University each contributed 11% to the survey.

It is seen that the participants who graduated from business administration (35%) and social sciences (21%) departments are more than half of the total participants (Figure 4).

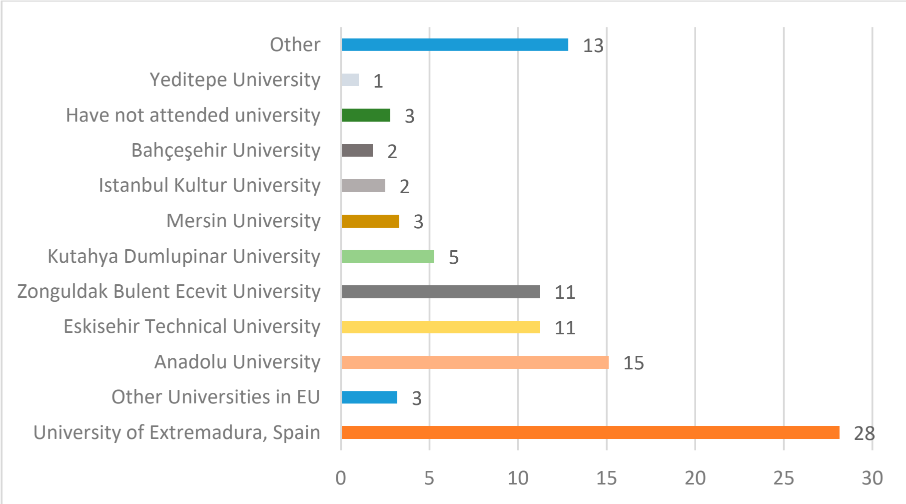

Figure 3. Distribution of Participants by University of Study (%). Source: Authors' calculations based on the primary data.

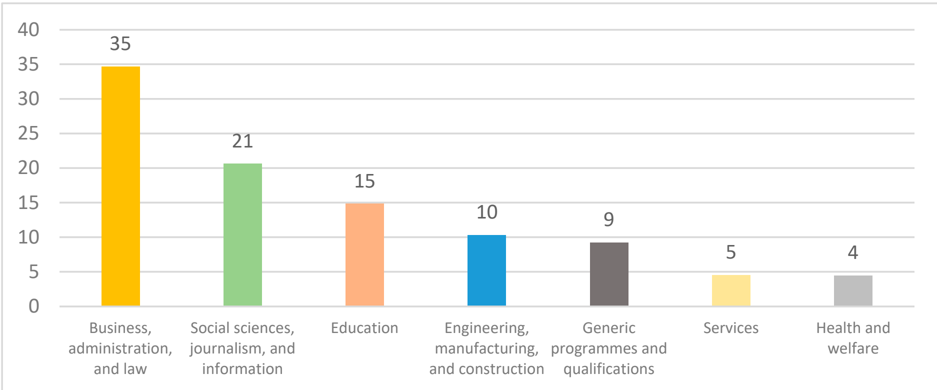

Figure 4. Distribution of Participants by Degree Subject (%). Source: Authors' calculations based on the primary data.

Figure 5 shows that most of the participants are students. Undergraduate and graduate students constitute 72.7% of the total number of respondents. The rates of employed, unemployed, and NEET are 17.6%, 6.9%, and 1.4%, respectively.

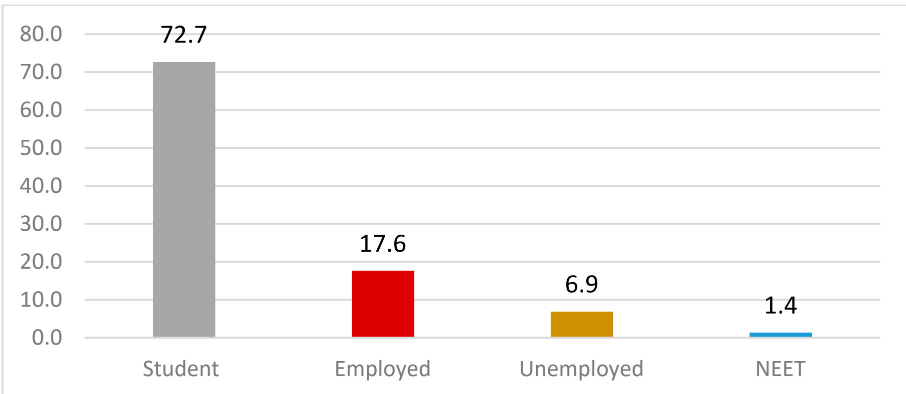

Figure 5. Employment Status of the Participants (%). Source: Authors' calculations based on the primary data.

Figure 6 and Table 1 show that 455 respondents are students, 115 respondents have a job, and 40 respondents are unemployed in Turkey. In Spain, 214 respondents are students, 56 respondents have a job and 28 people are unemployed. In Portugal, 17 respondents are students, 3 respondents have a job, and 1 respondent is unemployed. A total of 90.1% of those in employment have a full-time job. In addition, 74% of participants employed report that their job is a graduate job.

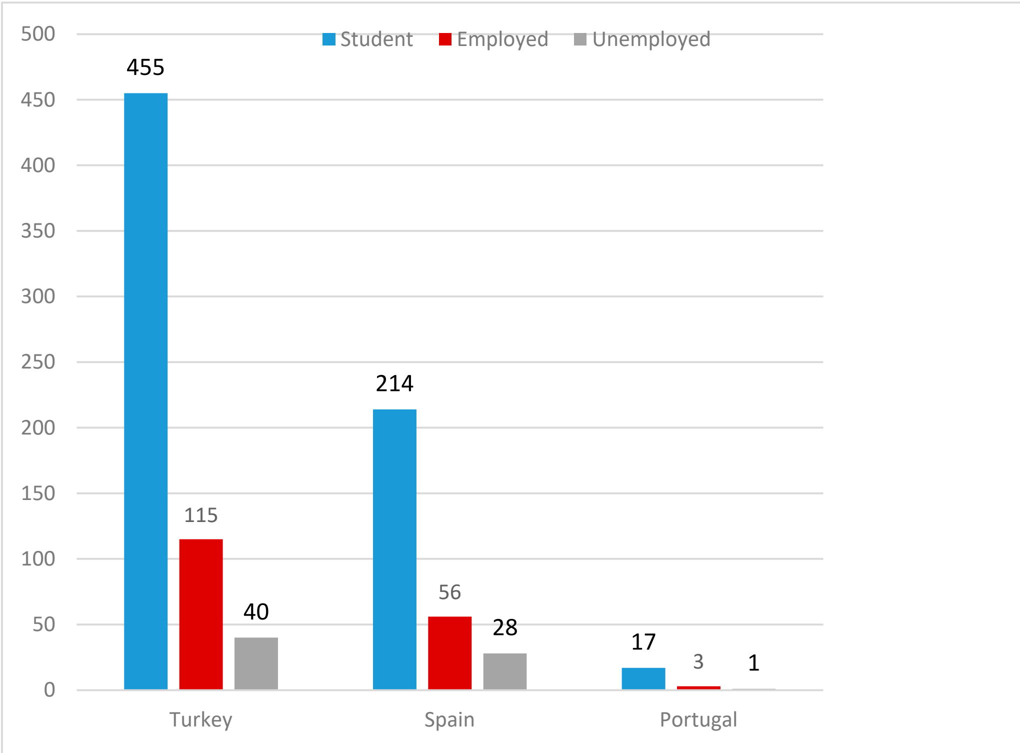

Figure 6. Employment Status of the Participants by Country. Source: Authors' calculations based on the primary data.

Table 1. Employment Status of the Participants by Country.

	Turkey	Spain	Portugal	Other Countries	Total
Student	455	214	17	62	748
Employed	115	56	3	7	181
Unemployed	40	28	1	2	71
Total	610	298	21	71	1000

Source: Authors' calculations based on the primary data.

Further data are reflected in the following findings. Among NEET participants, 78.6% have never had a job before, while 21.4% have some work experience. In terms of income, 79% rely primarily on their parents, whereas 7% report their partner as their main provider. With respect to career support, only 15% of respondents have received mentoring services, indicating that the vast majority of young people lack such guidance. Regarding technology use, 23% of respondents (236 individuals) stated that they employed artificial intelligence tools in their job search process. Among these tools, ChatGPT was the most commonly used, followed by LinkedIn, AI-powered job search websites, chatbots, and AI-based career assessment tools. Concerning perceptions of AI use, 49% of participants who utilized these tools found them somewhat useful, 32% considered them very useful, 12% remained undecided, and 7% reported that they did not find AI helpful in their job search.

The respondents have a generally positive view that AI plays an important role in the job search process. 663 respondents agreed with the statement 'AI is a valuable tool for job seekers and professionals looking to enhance their skills', which emphasizes the importance of AI in the skills development process. Similarly, 565 people agreed with the statement that AI helps in exploring job opportunities according to personal skills and preferences. Furthermore, 609 respondents agreed that AI speeds up the job search process and saves time, while 665 respondents agreed that AI provides valuable insights on industry trends and in-demand skills. All these results reveal that AI is seen as a useful tool by the participants, both in individual skill development and in the process of finding a job. However, the fact that more than 200 respondents chose 'don't know' in each statement indicates that there is still a lack of knowledge or uncertainty about the potential of AI in the labor market.

4. Model and Estimation Results

To answer the research questions, a survey was designed. In this respect, ethical approval was obtained from the Scientific Research and Publication Ethics Committee of Anadolu University prior to the survey implementation. To ensure the validity of the instrument, the questionnaire was reviewed by field experts, and a pilot study involving 124 participants was conducted to test its clarity and applicability. The final survey was then carried out with 1039 participants.

Prior to conducting the regression analysis, the reliability of the questionnaire was investigated. The internal consistency of the multi-item constructs was examined using Cronbach's alpha. The overall Cronbach's alpha coefficient was 0.9105, indicating a high level of internal consistency and reliability of the multi-item constructs employed in the questionnaire. Pseudo R^2 values of 1 indicate a perfect fit, while values above 0.2 are generally considered acceptable [54].

When the dependent variable is binary, estimation via the ordinary least squares (OLS) method is inappropriate, as it does not yield consistent or efficient parameter estimates. In such cases, models are typically estimated using the maximum likelihood approach, which requires explicit distributional assumptions regarding the error term. The Probit model assumes a standard normal distribution of errors, whereas the Logit model is based on the logistic distribution.

We aim to use both the Logit model and Probit model to capture the factors affecting education–job mismatch. This study utilized the education–employment mismatch measure operationalized in the Erasmus+ KA2 project titled "EMLT Module Distance Education System as a New Product for Reducing the Education–Job Mismatch in the European Area," which was successfully completed under the leadership of Prof. Dr. Nilgün Çağlarırmak Uslu. The model adapted in this Project can be written as follows:

$$Mi = \alpha + \beta' X + \varepsilon i$$

Mi = 1 if there is mismatch; Mi = 0 if there is no mismatch. α is a constant term, β is the vector of coefficients related to the explanatory variables. ε is the error term, which has logistic distribution in Logit model, while it has normal distribution in Probit model. The dependent variable of the mismatch equation is a dummy variable from the question "What field of study do you feel is most appropriate for this job?". The dependent variable takes the value of 1 if the answer is "Exclusively my own field of study", or "My own or closely related field of study". It takes the value of 0 if the answer is "A completely different field of study", "No particular field of study", or "Don't know". Table 2 presents the independent variables used in the analysis. Table 3 presents the estimation results of the Logit and Probit models.

Table 2. The Explanatory Variables Used in the Estimation.

Independent Variable	Question	Value
Female	What is your gender?	1 if ‘female’; 0, otherwise
Married	Marital status	1 if ‘married/civil partnership’; 0, otherwise
Children	Do you have any children?	1 if ‘yes’; 0, otherwise
Age	What is your age?	1 if age > 30; 0, otherwise
Livingparent	Who do you live with?	1 if ‘with my parent(s)/relative(s)’; 0, otherwise
Masterdegree	What is the highest degree you receive?	1 if ‘master’s degree/PhD’; 0, otherwise
Internship	Did you take part in any internships?	1 if ‘yes’; 0, otherwise
Language	Did you learn any foreign languages at university well enough to use for work related purposes?	1 if ‘yes, one/yes, more than one’; 0, otherwise
Privatesector	Is it located in the public or private sector?	1 if ‘private sector’; 0, otherwise
Graduatejob	Is your current job a graduate job?	1 if ‘yes’; 0, otherwise
Passionatesubject	Why did you choose your degree subject?	1 if ‘I was passionate about my subject’; 0, otherwise
Wouldchoose	If you could choose any job, would it be your current job?	1 if ‘yes’; 0, otherwise
Matchedu	What level of education do you feel is most appropriate for your current job?	1 if ‘Bachelor’s degree/Master’s degree/PhD’; 0, otherwise
Mentorship	Have you received mentoring services before?	1 if ‘yes’; 0, otherwise
Aiusage	Have you ever utilized artificial intelligence (AI) in your job search process?	1 if ‘yes’; 0, otherwise
Reskilljob	Motivated to reskill	1 if ‘to find a job’; 0, otherwise
Reskillown	Motivated to reskill	1 if ‘to start my own business or become an entrepreneur’; 0, otherwise

Table 3. The Results of the Logit and Probit Models.

Dependent Variable: Match	Probit Model	Logit Model
Female	−0.1416675	−0.3352867
	(0.262)	(0.509)
Married	−0.3583068	−0.5571015
	(0.367)	(0.764)
Children	−0.2626325	−0.5307475
	(0.461)	(0.921)
Age	0.4962012	0.9736421
	(0.418)	(0.814)
Livingparent	−0.0865987	−0.175523
	(0.314)	(0.596)
Masterdegree	0.5891255 *	0.9274989
	(0.302)	(0.576)
Internship	0.116178	0.408425
	(0.287)	(0.555)
Language	−0.085964	−0.1772354
	(0.258)	(0.496)
Privatesector	0.1079073	0.1650131
	(0.269)	(0.559)

Table 3. *Cont.*

Dependent Variable: Match	Probit Model	Logit Model
Graduatejob	1.039716 ***	1.894089 **
	(0.387)	(0.791)
Passionatesubject	0.2288515	0.4049477
	(0.287)	(0.584)
Wouldchoose	0.9667371 ***	1.789843
	(0.287)	(0.539)
Matchedu	0.3392726	0.4576121
	(0.419)	(0.828)
Mentorship	−0.1883939	−0.3500142
	(0.385)	(0.816)
Aiusage	−0.128408	−0.2328541
	(0.388)	(0.744)
Reskilljob	0.2306891	0.3679461
	(0.273)	(0.506)
Reskillown	0.2726748	0.5290958
	(0.285)	(0.563)
Constant	−0.9046078	−1.580362
	(0.555)	(0.106)
Observations	181	181
Pseudo-R^2	0.2593	0.2472
Prob > chi2	0.0002	0.0032

Robust standard error in parentheses. ***, **, and * denotes 1%, 5%, and 10% significant level, respectively.

Individuals working in positions requiring at least a bachelor's degree were found to be more likely to be working in jobs compatible with their field of study. This indicates that requiring a specific academic qualification in the job description favors field matching. Since positions requiring graduation generally demand more specific knowledge and skill sets, individuals are more likely to be employed in fields that overlap with their educational background.

According to the results of the Logit and Probit models, those who stated that they would choose their current job if they had the chance to choose any job have a higher probability of being matched. This finding reveals that field compatibility is not only an objective matching criterion, but also meaningful in terms of individual preferences and job satisfaction. This relationship may be explained by the fact that individuals have drawn their career paths with conscious preferences or that working in jobs suitable for their fields increases their sense of satisfaction. In conclusion, education–job matching is an important factor that should be considered not only in terms of labor productivity but also in terms of individual happiness and motivation.

The obtained findings from the Probit model show that having at least a master's degree has a positive effect on being matched. This suggests that master's degree education makes individuals more specialized in a particular field, enabling them to establish a stronger connection with job opportunities specific to that field. In addition, the fact that higher levels of academic education are one of the reasons why employers prefer higher levels of academic education for certain professional positions may also support this alignment. This finding suggests that the level of education increases not only the individual's knowledge but also his/her chances of being employed in field-compatible jobs in the labor market.

Our findings are consistent with and extend current research on education–employment mismatch. Prior studies show that higher educational attainment and specialization reduce mismatch risks by improving skill–job alignment [32,33], which supports our result that holding a master's degree and working in positions explicitly requiring a degree increases field alignment. At the same time, while recent work highlights the potential of algorithmic recommendations and AI-based platforms to improve labor market matching [55,56], our results indicate that current AI use in job search has limited impact. This suggests that AI tools are still in an early stage of effectiveness and need to be complemented by mentoring and structured guidance.

5. Conclusions

Education–job mismatch is the situation where an individual's level of education, skills and area of specialization do not match the qualifications required by the job. This mismatch is a major obstacle to individual welfare, organizational productivity, and social development. Regarding Human Capital Theory [29,30], these mismatches can be interpreted as market inefficiencies. At a macro level such mismatches limit the growth potential of an economy due to inefficient use of the human capital. Human capital theory views education, training, and experience as investments that enhance productivity and generate economic returns. Ideally, this implies a close alignment between workers' skills and labor market needs. In reality, however, skill mismatches—where individuals are over- or underqualified relative to job requirements—are common due to technological change, structural economic shifts, and uneven access to training. Such mismatches reduce the efficiency of human capital investments, as overskilled workers face underutilization and wage penalties, while underskilled workers encounter barriers to better jobs. This divergence challenges the assumption that human capital investment automatically yields productivity gains, highlighting the importance of institutional and policy frameworks that better link education and training with evolving labor market demands. Moreover, individuals working in jobs outside their field of education often face job dissatisfaction, low motivation, and limited development opportunities. Similarly, employers face lost productivity, high staff turnover and increased costs due to employees whose qualifications do not match the requirements of the job. Hence, the aim of this project is to decrease education–job mismatch by using artificial intelligence, which suggests suitable jobs for every targeted individual who uses the EMLT-AI system that presents a mentor pool and training courses. For this purpose, the total number of people interviewed in the project is 1039, of which 181 are employees. To identify the determinants of education–job mismatch, a total of 1039 people, 181 of whom were employees, were surveyed.

According to the results of the empirical analysis, individuals with master's or PhD level education are found to work in jobs that are more compatible with their fields. This finding reveals that specialization has a positive effect on education–job matching. Similarly, individuals working in positions defined as "graduate jobs" (jobs requiring a bachelor's degree) are found to be employed in jobs that are more compatible with their fields of study. This suggests that in positions where employers demand certain levels of education, individuals are employed in line with their areas of specialization and thus achieve a higher level of career matching. In addition, the fact that individuals make conscious choices regarding their career choices stands out as another factor that positively affects education–job fit. It was found that the participants who said "If I had the opportunity, I would choose this job again" were working in jobs compatible with their field of education. This shows that personal satisfaction stems not only from the quality of the job, but also from its compatibility with the individual's professional orientation. This result is in line with recent research as well [21,57,58]. Therefore, individual preferences and awareness should be systematically supported in sustainable career planning.

The project also found that there is a significant gap in access to mentoring services. The fact that only 15% of the participants received mentoring services in the past reveals that young people do not receive adequate guidance and support in career planning and finding a job. On the other hand, the fact that 66% of the respondents would like to receive mentoring services shows how high the demand for such support is among young people. This demand is particularly concentrated in the areas of career development and entrepreneurship, indicating that young people need guidance not only to be directed to available job opportunities, but also to structure their own career journeys and realize their business ideas. Mentoring services play a vital role in enabling individuals to know themselves, discover their potential and take strategic steps to achieve their goals. In this context, career guidance for young people is not only about transferring information, but also a multifaceted learning experience that strengthens self-efficacy, motivates, and supports informed decision-making. Recent research also points out the relevance of focused mentoring opportunities in tackling skills mismatches [59,60]. Therefore, making mentoring systems more systematic, accessible, and personalized in future projects will be a key element in building sustainable careers for young people. In terms of reskilling, most of the participants were motivated to reskill by the motivations of finding a job and starting their own business.

This shows that today's labor market is not only diploma-based but also competency-based. Career development, entrepreneurship, personal development, technology, and finance are the main areas where young people are developing themselves. This diversity reveals that the business world now demands flexible and adaptable individuals with interdisciplinary skills. Moreover, this trend shows that it is not enough to be equipped with technical knowledge alone, but that being prepared for ever-changing market conditions and technological transformations needs to be mainstreamed. Therefore, future projects should aim not only to provide skills but also to increase individuals' capacity to adapt to change through flexible, up-to-date and personalized training content.

In conclusion, the EMLT + AI project has made a significant contribution as an innovative step in the integration of young people into the workforce. However, for this contribution to be permanent and sustainable, there is a need to develop a new career training model that is individualized, competency-based and supported by artificial intelligence. In this sense, the focus of the next project will be on the construction of a comprehensive education model that will enable young people not only to be placed in jobs, but also to develop a sustainable career. This model will be based on AI-supported individual career recommendations, skill-based modular training contents and lifelong learning approach. It will be aimed to develop the competencies that participants will need in the business world of the future, such as digital skills, entrepreneurship, problem solving and communication. The new project to be designed in this direction will ensure that young people are prepared not only for the current labor market, but also for areas that are transforming and shaping the future.

The findings underscore the importance of structured mentoring and flexible skill development programs as complementary mechanisms to AI-based guidance. By combining personalized support with adaptive training, these measures can significantly enhance employability, strengthen resilience in the labor market, and foster inclusive career opportunities.

This study also carries important practical implications for multiple stakeholders. For educators, the findings underscore the importance of embedding employability training and career guidance within curricula, thereby equipping students with both technical and transversal skills that are directly aligned with labor market demands. Career advisors can benefit from complementing traditional counseling with AI-assisted systems such as EMLT + AI, which provide tailored recommendations based on individual aptitudes, interests, and real-time labor market dynamics. This hybrid approach improves the accuracy and relevance of career advice. Finally, for policy makers, the results point to the need for policies that foster closer collaboration between educational institutions and employers, encourage the adoption of data-driven tools for labor market forecasting, and allocate resources to continuous reskilling initiatives. Collectively, these measures can mitigate education–job mismatch, enhance youth employability, and contribute to building a more adaptive and inclusive workforce.

The study also has some limitations. As this study was designed as an exploratory investigation, it does not include the formal testing of predefined hypotheses. While this approach enabled us to map the phenomenon, identify salient patterns, and generate novel insights, it also limits the extent to which causal inferences or generalizable conclusions can be drawn. Future research should build on these findings by developing and empirically testing specific hypotheses through confirmatory designs.

In addition, and despite using a comprehensive sample, the employed and NEET subsamples are relatively small. Future research could examine the determinants of education–employment mismatch in greater detail by using samples with a larger number of employed and NEET participants, as well as a more balanced distribution of countries and institutions. This could be achieved either by continuing with the same logit/probit model family or by using alternative models (e.g., multilevel or ordinal/multinomial). This would also strengthen the generalizability of the results.

6. Patents

For further details on the implementation processes of the EMLT + AI system, please visit https://emltai.eu (accessed on 22 September 2025) You may access and interact with the platform by logging in at https://app.emltai.eu/sign-in (accessed on 22 September 2025).

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Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

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